Out with the power outages: Peak load reduction in the developing world

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Abstract: In developing economies with hot climates, the summer time peak load due to space cooling frequently results in power outages, as the outdated grid is not able to keep up with the demand. In this paper, computer simulation is carried out to develop and analyse a two-pronged strategy for peak load reduction, utilizing a relatively new thermal comfort model, together with variation in building fabric properties. The thermal comfort model is used to dynamically set the cooling setpoint temperature through implementation in MATLAB, with the building is simulated using EnergyPlus V8.8, both linked for co-simulation using the Buildings Control Virtual Test Best (BCVTB).

Compared to the baseline with a typical fixed cooling setpoint of 24°C, the newly developed cooling setpoint control strategy resulted in a reduction of 20% and 41% in the peak load and monthly energy demand respectively. This came at the cost of increasing the average PPD% from 7.2% to 12.6%. This work may be of interest to practitioners wishing to address demand management at the building scale. Moreover, it may be readily extended to analyse a group of buildings towards demand management at a higher level of aggregation.

Keywords: Peak load shaving, Demand response, Buildings Energy Efficiency, Space cooling, Dynamic thermal comfort

1. Introduction

Over the recent decades, energy use in buildings within the context of global warming and environmental sustainability has attracted much attention from researchers, practitioners and policy makers alike. This sustained focus is because the building sector is responsible for about one-third of the global final energy use, with projections of further increase (Takahashi *et al.*, 2014)

India is a developing economy where the Per Capita energy use is increasing by 3.3% every year (CSO, 2016), and its population is projected to reach 2.3 billion by 2080 (UN, 2016). In summer time, many parts of India experiences extreme temperatures that translates to high peak cooling energy demand within buildings. Coupled with the fact that India, much like other developing countries, has a fragile energy network, results in power outages ranging from 3 to 30 hours per month at peak summer conditions (Prayas Gr., 2016). Such power outages result in unacceptable levels of thermal comfort, leading to many fatalities at peak summer conditions (Chung *et al.*, 2018). For these reasons, addressing this issue of peak energy demand if of significant importance in India and other developing countries with similar climate. To tackle this issue, this paper presents an implementation of a strategy that combines (i) thermal comfort based control of the cooling systems with (ii) variation in the building fabric's thermal mass and thermal resistance. In the following sections, both these concepts are reviewed within the context of developing a peak load reduction strategy at the building level.

2. Thermal comfort

Thermal comfort is defined as "that condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation" (Turner *et al.*, 2008). To achieve this occupant thermal comfort, the indoor environmental space is conditioned by employing Heating, Ventilation and Air Conditioning (HVAC) systems.

The most commonly used thermal comfort metrics are the Fanger's PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied), developed in 1970 by Ole Fanger, and then adopted into a number of international thermal comfort standards (Carlucci *et al.*, 2018). Concisely referred to as Fanger's PMV/PPD model, it is based on experiments that assume stead state conditions within the indoor building space, and implies that occupants do not really adapt to their thermal environment. While this assumption holds true for tightly conditioned spaces, many studies have shown that occupants do indeed adapt to changing thermal environments, and that the perceived occupant satisfaction is not dictated by as stringent space conditioning as demanded by Fanger's PMV/PPD model (A *et al.*, 1999; Han *et al.*, 2007). These reasons led to the development of the adaptive thermal comfort theory, where human physiology, phycology and behavioural change is believed to induce adaptation in thermal comfort due to temperature fluctuations. The adaptive occupant thermal comfort can be predicted through a simple linear relationship between the indoor operative temperature and outdoor environmental conditions. Figure *1* depicts this relationship as defined by the ANSI/ASHREA 55:2017 thermal comfort standard (Turner *et al.*, 2008). Here, an acceptable thermal comfort band for the indoor operative temperature is defined based on the prevailing mean outdoor air temperature. Similarly, several other global standards have incorporated variations of the adaptive comfort model, as documented by (Carlucci *et al.*, 2018).

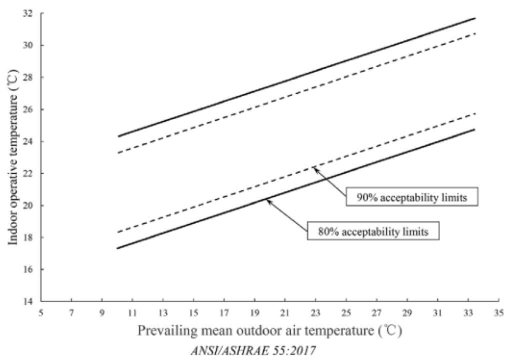

Figure 1 – ANSI/ASHREA 55:2017 adaptive thermal comfort model (Turner et al., 2008)

While the adaptive thermal comfort theory acknowledges people's adaptation to temperature fluctuation, its application is limited to slowly changing environments only (diurnal or seasonal temperature variation). In demand response (DR) strategies, building space conditioning equipment may be periodically turned 'on' and 'off', resulting in short-term cyclical variations. Consequently, Vellei and Le Dréau (2019) argue that neither Fanger's PMV/PPD model, nor the adaptive comfort models are suitable to assess occupant thermal comfort during such cyclical variations.

To address this gap, Vellei and Le Dréau (2019) developed a new model to gauge thermal comfort during short term cyclical variations in temperature, by adding a transient component to the Fanger's PMV based static model, to account for thermal alliesthesia and thermal habituation/adaptation. Alliesthesia has been defined as "the property of a given stimulus to arouse pleasure or displeasure according to the internal state of the subject" (Cabanac, 1979). Within the thermal environment, when a stimulus induces a pleasant perception, it is termed as positive alliesthesia. Similarly, negative alliesthesia is characterised by an unpleasant sensation. The magnitude of alliesthesia corresponds to (i) variation from thermal neutrality (PMV = 0) and (ii) Rate of change of skin temperature. Thermal habituation/adaptation is the phenomenon when sensory perception of humans reduces as they are exposed to repeated thermal exposures. Within the context of temperature fluctuations induced by DR events, exposure to repeated cycles of indoor air temperature variations of similar magnitude and shape would increase thermal habituation/adaptation within the occupants. In Vellei and Le Dréau (2019)'s model, thermal habituation/adaptation is quantified as follows

$$exposure = \sum_{cycle} (PMV - PMV_{min})^2 dt \; [discomfort^2 \; minutes]$$

Where,

$$PMV_{min} = minimum \; PMV \; reached \; at \; each \; cycle; or \; zero \; if \; negative$$

Vellei and Le Dréau (2019)'s model is based on Fanger' PMV and defines a new PPD indicator, which is referred to as 'VPPD' in the remainder of this paper, given by the following equation. The constants a,b,c and d are regression coefficients derived from experimental data and quantify the impact of alliesthesia in the thermal comfort model.

$$VPPD = 100.34 + \left\{a * abs\left(\frac{dPMV}{dt}\right) + b * exposure - 96.93\right\} * e^{(-0.03*PMV^4 - 0.23*PMV^2)} + c * abs\left(\frac{dPMV}{dt}\right) + d * exposure$$

$Where,$

$$\left(for \; \frac{dPMV}{dt} < 0\right): a = 10.12h, b = 0.14 \; min^{-1}, c = -10.59h, d = -0.14 min^{-1}$$

$$\left(for \; \frac{dPMV}{dt} > 0\right): a = -3.34h, b = 1.17 \; min^{-1}, c = 4.68h, d = -1.18 min^{-1}$$

$$\left(for \; \frac{dPMV}{dt} \simeq 0\right): a = -20.56h, b = 0.65 \; min^{-1}, c = 19.16h, d = -0.7 min^{-1}$$

A key finding of this model was that humans are sensitive to the rate of cooling, while for heating, it is the absolute value of temperature rather than its differential that mainly impacts alliesthesia. This means that for the range of temperatures expected during DR events, humans are more sensitive to cooling, than to heating. This is justified by the way in which cold and heat perception neurons operate in the human body (Ran, Hoon and Chen, 2016). Consequently, for unsteady indoor environment conditions as in DR events, the acceptable limit of thermal comfort based on the VPPD indicator corresponds to a PMV of up to 1.5, compared to a PMV of 0.85 for the Fanger model. Therefore, the VPPD metric may allow a greater fluctuation in indoor air temperature as compared to Fanger's PPD without compromising thermal comfort. This makes it suitable for use as a control variable for the cooling systems, as the larger permitted temperature fluctuation would promote reduced air conditioning without compromising occupant thermal comfort. Controlling HVAC thermostats based on thermal comfort indicators have been shown to reduce energy demand of buildings. For example, (Saffari *et al.*, 2016) employed Fanger's PMV based temperature setpoint control to evaluate the economic impact of incorporating Phase Change Materials (PCMs) in the building. However, the Fanger's PMV/PPD based approach would not suit HVAC control for a DR strategy with short-term temperature fluctuations, as it is applicable only to steady state or slowly changing systems. Therefore, in such a situation, it is pertinent to use VPPD as a control variable for HVAC thermostat control, the detail of which is presented in Section 5.3.

3. Thermal mass

Thermal mass in buildings is the ability of the building mass to absorb and store thermal energy. In heavy weight buildings, the walls and roof may have the ability to store enough energy so as to reduce temperature fluctuations on the inside surface, and shift the peak load to a later time in the day. Therefore, thermal mass based strategies have been employed in several studies as a load shifting strategy (Lee and Medina, 2016; Saffari *et al.*, 2016). Typically, either the thickness or the material, which corresponds to thermal conductivity, in the building envelope is varied or other technologies such as PCMs are utilised to increase the energy storage capacity of the building. For example, Tyagi et. al., (Tyagi *et al.*, 2016) used PCMs to shift peak time cooling energy demand to off peak time. However, Al-Sanea et. al., (Al-sanea and Zedan, 2011) point out that it is not only the thermal mass, but also the thermal resistance that impacts the peak shifting ability of buildings. An insulation material may not have much energy storage capacity, but its high thermal resistance delays the heat transmission to or from the indoor space, thus delaying heat transmission. Therefore, it is important to consider thermal resistance as well as thermal mass when developing a peak load reduction strategy. Based on the reviewed literature, a clear research objective is defined in the section that follows.

4. Research objective

From the reviewed literature in the preceding sections, the following observations are made within the context of developing a peak load reduction strategy.

- Fanger's PMV/PPD, and the adaptive thermal comfort models are not well suited to gauge occupant thermal comfort during DR events that impose short-term cyclical temperature variations on the indoor space. Vellei and Le Dréau (2019) developed a thermal comfort model that is designed specifically for assessment of occupant thermal comfort in such conditions. As it includes additional transient terms to that of Fanger's PMV/PPD model to account for thermal alliesthesia and thermal adaptation, it is sensible to develop a VPPD based peak load reduction strategy.

- A key finding of Vellei and Le Dréau (2019)'s model was that humans are more perceptive to cooling than to heating. This is because our coolth receptive neurons respond more to the rate of change in cooling, while our heat receptive neurons respond to the absolute temperature change. Consequently, Vellei and Le Dréau (2019)'s model defines a broader thermal comfort range for the indoor air temperature as compared to Fanger's model. Thus, utilising VPPD as a control variable to establish cooling setpoint temperatures dynamically may result in lowering the average and peak demand.
- Heat transmission to the indoor space may be delayed with increasing thermal mass and thermal resistance of the building fabric. Therefore, including these tactics may lead to lower peak loads.

Based on the above observations from literature, the following research objective is defined for this work,

"To implement and investigate a peak load reduction strategy that combines (i) VPPD based control of the cooling systems and (ii) Thermal mass and thermal resistance variation in the building fabric."

5. Methodology

5.1 Overview

This study employs a simulation-based approach to analyse the peak reduction capability of the newly developed VPPD based approach. The case study building is a residential apartment complex in New Delhi, India (see Section 5.2 for detail on the modelling and validation). The reason for selecting a residential building is that domestic electricity use dominates the buildings energy demand in India. In 2015 -2016, the electricity demand of the residential sector in India was 24% of the total electricity use in the country. Furthermore, it is projected to increase as more households are expected to adopt air conditioning which is a consequence of economic growth (Chunekar and Sreenivas, 2019). Following detail on the case building and its considered variants (Section 5.2), a description of the different cooling setpoint control strategies is presented in Section 5.3, to be applied to the different building variants. The results and analysis are presented for a single controlled zone, which corresponds to a single bedroom within an apartment. Finally, the results are extrapolated to the building level to quantify the impact of the developed peak reduction strategy at the building scale.

5.2 Case building and its variants

A typical Indian two bedroom apartment residential building was modelled with EnergyPlus v.8.8 as defined by the Global Building Performance Network, GBPN (Rajan *et al.*, 2014a). It is a two-story building with four apartments on each floor, with a total covered area of 330m^2. Figure *2* (left) presents the building's overview while Figure *2* (Right) presents one apartment.

Within each apartment, the drawing room and bedrooms are serviced as separate zones using individual Packaged Terminal Air Conditions (PTAC). The occupancy is set to 0.11 people/m^2 corresponding to four people per each 41.25m^2 apartment. The weather file used is for middle Delhi (Chung *et al.*, 2018), while the simulation with a time-step of one minute was carried out for May, which has the highest monthly average and peak temperatures. To compare the impact of the different cooling setpoint control strategies, a single bedroom was selected (Figure *2* (Right)). For investigating the impact of building characteristics on thermal comfort, the thermal mass and thermal resistance were adjusted for the typical building based on the work done by Ramesh, Prakash and Shukla (2012).

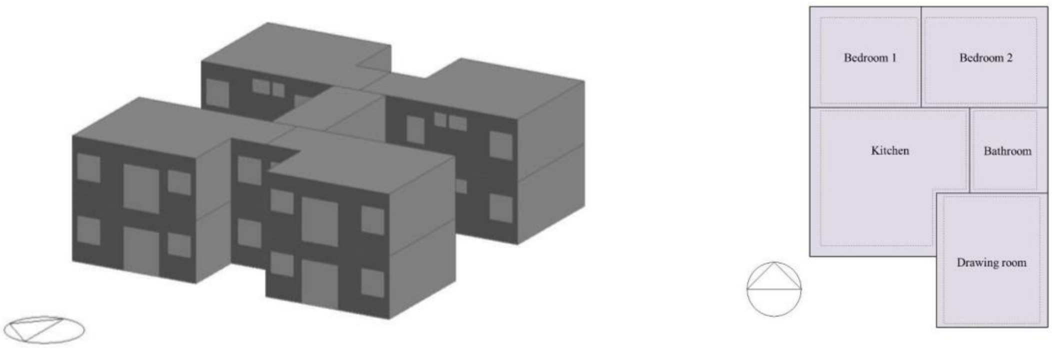

Figure 2 - Building overview (left), Apartment plan view (Right)

To assess the impact of varying thermal resistance within the building envelope, the 'Business as Usual' (BAU) and the 'Energy Conservation Building Code Plus' (ECBC+) building variants defined by the GBPN (Rajan *et al.*, 2014b) have been considered. The BAU parameters are representative of a typical building envelope in India, while the ECBC+ is representative of an energy efficiency envelope, selected in view of economic considerations (Rawal *et al.*, 2012). This leads to the definition of four building variants, with their parameters provided in Table *1*

Table 1 - Building variants considered in this study

	Low thermal resistance (BAU)	**High thermal resistance (ECBC+)**
Light Weight	Wall thickness = 0.13m U-value wall = 1.72 U-value roof = 2.94 U-value floor = 2.94 U-value Window = 5.8	Wall thickness = 0.13m U-value wall = 0.35 U-value roof = 0.41 U-value floor = 0.25 U-value Window = 3.3
Heavy Weight	Wall thickness = 0.43m U-value wall = 1.72 U-value roof = 2.94 U-value floor = 2.94 U-value Window = 5.8	Wall thickness = 0.43m U-value wall = 0.35 U-value roof = 0.41 U-value floor = 0.25 U-value Window = 3.3

5.3 Cooling setpoint control strategies

As the focus of the analysis in on peak load conditions, which is typically mid-afternoon in summertime, natural and mixed mode strategies are expected to lead to uncomfortable conditions. Therefore, only cooling setpoint control strategies suitable for mechanical mode is considered below,

5.3.1 Static set point of 24°C

Ghawghawe et al., (2014) analysed static cooling setpoint temperature in relation to the A/C systems COP and thermal comfort for a number of cities in India. They concluded that a static setpoint temperature of 24°C is a typical setpoint which results in comfortable conditions for New Delhi, and is considered here as the baseline cooling setpoint strategy.

5.3.2 IMAC (Indian Model for Adaptive Comfort)

This model is based field studies across several cities in India and is valid for buildings operating in AC mode. Based on the field studies, it was found that Fanger's PMV/PPD model or the adaptive comfort models of ASHREA 55 and EN15251 overestimated the occupant discomfort (Manu *et al.*, 2016). As the IMAC model is based on empirical data from the Indian context, it can be employed within India. It is valid within the outdoor running mean temperature range 13°C – 38.5°C and is given by (Angelopoulos *et al.*, 2018),

$$T_{HSP} = 0.28 * \ T_{out} + 14.4$$

$$T_{CSP} = 0.28 * \ T_{out} + 21.4$$

Where, T_{HSP} , T_{CSP} and T_{out} are the heating setpoint, cooling setpoint and outdoor running mean temperature respectively. This model is implemented using the Building Control Virtual Test Bed (BCVTB), to link MATLAB with EnergyPlus V 8.8. At each time step, the free running monthly mean outdoor air temperature was calculated based on which the preceding equation was used to calculate and communicate the cooling thermostat setpoint temperature to EnergyPlus.

5.3.3 Static VPPD

In this approach, the cooling setpoint is controlled indirectly through the VPPD metric, by keeping it less than 10%, corresponding to the ASHREA 90% thermal comfort acceptability limit. This was implemented by using the BCVTB, to link MATLAB with EnergyPlus, through the thermal comfort based Fanger's PMV setpoint control available in EnergyPlus. The steps to accomplish this using the BCVTB are as follows,

I. Retrieve Fanger's PMV in MATLAB for the current timestep
II. Implement conditional statements to keep VPPD just under 10% based on Vellei and Le Dréau (2019)'s model as depicted in Figure 3, to generate the setpoint PMV
III. Communicate the Setpoint PMV to EnergyPlus for the next timestep

Figure 3 shows that for a PMV differential of up to 1 vote/hour, Fanger's PPD and VPPD are almost exactly the same. This is because in such conditions, the transient component in the VPPD metric approaches zero. On the warm side of the thermal neutral plane, and where positive alliesthesia is stimulated (indicated by 'P'), Figure 3 shows that the variation between the two models is directly proportional to the rate of change of PMV. For example, in the case where the PMV differential is 6 votes/hour or greater, PPD = 10% corresponds to PMV=1.1 for Vellei and Le Dréau (2019)'s model while the same limit corresponds to PMV=0.4 for

Fanger's model. To implement the static VPPD setpoint control strategy, the following conditions were used, corresponding to step II above.

$$PMV\ setpoint = \begin{cases} \dfrac{dPMV}{dt} < -4 & -0.55 \\ -4 < \dfrac{dPMV}{dt} < -1 & -0.5 \\ 4 < \dfrac{dPMV}{dt} < 1 & 0.5 \\ \dfrac{dPMV}{dt} < 1 & 0.5 \\ 4 < \dfrac{dPMV}{dt} < 1 & 0.85 \\ \dfrac{dPMV}{dt} > 4 & 1.1 \end{cases}$$

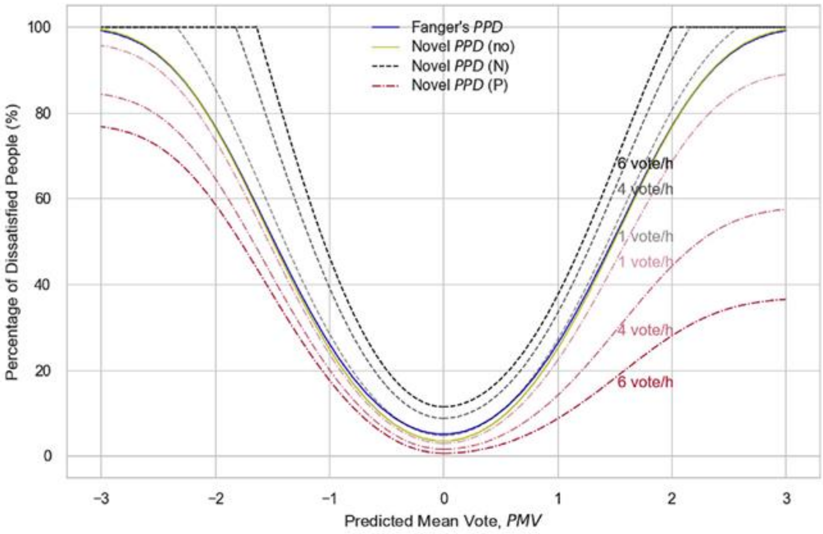

Figure 3 - VPPD% based on the absolute value and rate of change of Fanger's PMV (Vellei and Le Dréau, 2019)

5.3.4 Switching VPPD

In this approach, the VPPD percentage is allowed to vary between 5% - 20%, to deliver an average VPPD comparable to the static VPPD approach. This is implemented through co-simulation using the BCVTB platform to link MATLAB and EnergyPlus in the following steps

I. Retrieve Fanger's PMV in MATLAB at the current simulation time step
II. Calculate VPPD base on the equations in Section 2
III. Implement conditional statements to decide AC systems switching on/off
IV. Communicate AC switching to EnergyPlus for the next timestep.

It should be noted that through the use of BCVTB and the steps defined above, a lag of one timestep is introduced, and thus the small simulation timestep of 1min was used uncomfortable conditions. For the same reason, the VPPD thresholds for switching the AC on/off was slightly offset from 5% and 20%. The conditional statement to decide AC switching are provided below,

$$AC\ Switching = \begin{cases} (VPPD > 18) \wedge (PMV > 0) & AC\ on \\ (VPPD \geq 10) \wedge (PMV > 0)\ \wedge \left(\frac{dVPPD}{dt} \geq 2\right) & AC\ on \\ (VPPD > 18) \wedge (PMV < 0) & AC\ off \\ (VPPD \geq 10) \wedge (PMV < 0)\ \wedge \left(\frac{dVPPD}{dt} \geq 2\right) & AC\ off \\ (VPPD < 8) & AC\ off \end{cases}$$

The peak load analysis presented in Section 6 is done based on peak load per zone. For this VPPD switching setpoint control strategy, it is assumed that while the AC system is off in one zone, another zone within the building will be serviced. For example, if two additional zones can be serviced before the AC system needs to turn on again, a total of three zones would be serviced in one cycle. Based on this logic, the peak load per zone is calculated as follows,

$$Total\ servicable\ zones = \frac{Total\ cycle\ time}{AC\ on\ time}$$

$$Peak\ loads\ per\ zone = \frac{Zone\ peak\ load}{Total\ servicable\ zones}$$

This essentially assumes that there are different zones within the building that can perfectly coordinate with each other to turn the AC systems On/Off in tandem. Consequently, a higher peak load with a sufficient ‘off’ period may reduce the peak load per zone in comparison with static VPPD or temperature setpoint strategies.

5.4 Comparison scenarios

Corresponding to Table *1*, the four building variants described in Section 5.2 are succinctly abbreviated as follows,

i. BAU LW – The business as usual lightweight building
ii. BAU HW – The business as usual heavyweight building
iii. ECBC+ LW – The ECBC+ lightweight building
iv. ECBC+ HW – The ECBC+ heavyweight building

Within each building variant, the four cooling temperature setpoint strategies are implemented as defined in 5.3, succinctly referred to in the remainder of this paper as follows:

a. Tset = 24 – Fixed cooling setpoint temperature of 24°C
b. IMAC – Dynamic cooling setpoint based on the IMAC model
c. Static VPPD - Dynamic cooling setpoint based on a static VPPD value just below 10%
d. Switching VPPD - Dynamic cooling setpoint based on VPPD ranging between 5% - 20%

Thus, in total, 16 scenarios have been defined. Tset = 24 is the baseline for the cooling setpoint strategies, while the BAU LW is the baseline building variant. Overall, the BAU LW with Tset = 24 is considered the baseline, which also the likely typical scenario in practice.

6. Results and Discussion

The analysis presented in this section is for a single zone corresponding to a 6.8m^2 bedroom, serviced by a PTAC unit. After the difference in performance for all the scenarios is quantified, the results are then extrapolated to the building level. To demonstrate the difference in operation between the different cooling setpoint control strategies, the indoor air temperature for a single zone over a typical day in May is presented in Figure 4. As the month of May has the highest peak temperatures over the typical reference year, a typical afternoon in May is considered as a representative peak summer afternoon, having a peak temperature over 40°C.

Other than the fixed temperature setpoint of 24°C, the remaining three setpoint control methods result in variable indoor air temperatures. According to the 'VPPD Static' method, the indoor air temperature varies over a small range between 27°C and 28°C. The 'IMAC' based control results in warmer indoor conditions, which varies between 28°C and 32°C in this case. However, it should be noted that the IMAC standard is based on thermal comfort data from field surveys in various Indian cities as opposed to the typical PMV/PPD or adaptive thermal comfort indicators. For the VPPD Switch control strategy, Figure 4 shows that a cyclical pattern develops, which is typical of DR events. Here, the temperature varies between 24°C and 29°C, to keep the VPPD thermal comfort indicator between 5% and 20%. In other words, the AC system is kept 'on' until a VPPD of 5% is reached, which corresponds to approximately 24°C in this example. The AC system is then kept off until the VPPD is just below the specified threshold (20%), corresponding to 29°C approximately in this example afternoon. These observations show that the four setpoint control strategies are behaving as expected, for which the peak load, energy demand and thermal comfort results are presented next.

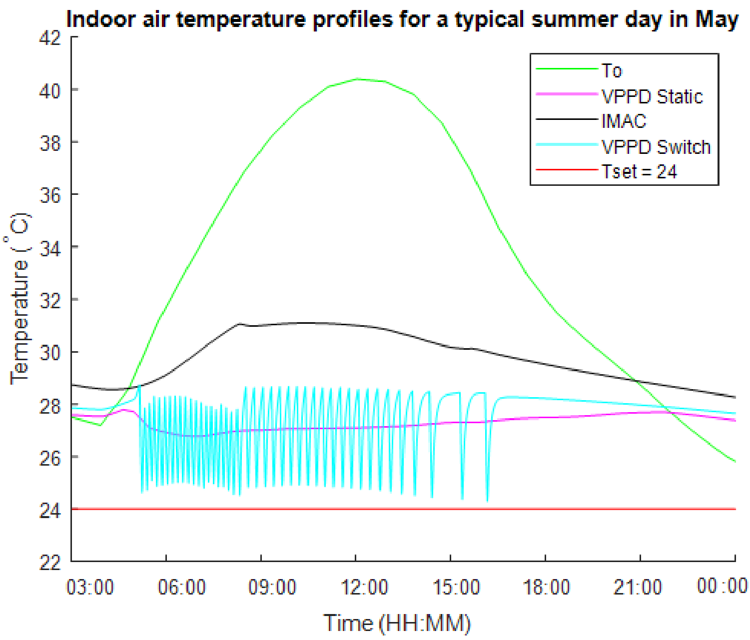

Figure 4 - Indoor air temperature on a peak summer afternoon for the difference setpoint strategies

Figure 5 depicts the daily peak loads in the Month of May for the analysed zone. The results are presented for the four setpoint control methods across the four building variants. First it can be observed that the IMAC and Tset = 24 setpoint control strategies result in the lowest and highest peak load respectively. Viewing this observation relative to the average thermal comfort, it is clear that the fixed 24°C strategy also leads to the highest levels of thermal comfort. Both the VPPD based schemes have comparable levels of average thermal comfort.

While the IMAC standard is not subject to the PMV/PPD thermal comfort model, the high levels of discomfort predicted by the VPPD indicator highlights this large gap between the predictions made through the PMV/PPD models, and observed field data. Considering that the VPPD ranges from 64% - 75%, such a high PPD% indicates that the current PMV/PPD based models are not able to accurately predict thermal comfort in extreme summer conditions, such as those observed in India. It should be noted here that the socioeconomic context is also important, and that this inability of the PMV/PPD model to accurately reflect the occupant's comfort may be impacted by the living standards that corresponds to a developing economy. Nonetheless, this issue may be investigated in future research to reconcile this difference.

Table 2 - Average thermal comfort across the 16 scenarios

Scenario	**Average Thermal Comfort (VPPD %)**			
	Tset = 24	IMAC	VPPD Static	VPPD Switch
BAU LW	4.9	74.8	9	11.9
BAU HW	4.2	71.6	9	11.1
ECBC+ LW	7.2	63.7	9.3	12.6
ECBC+ HW	4.8	68.5	9	12.8

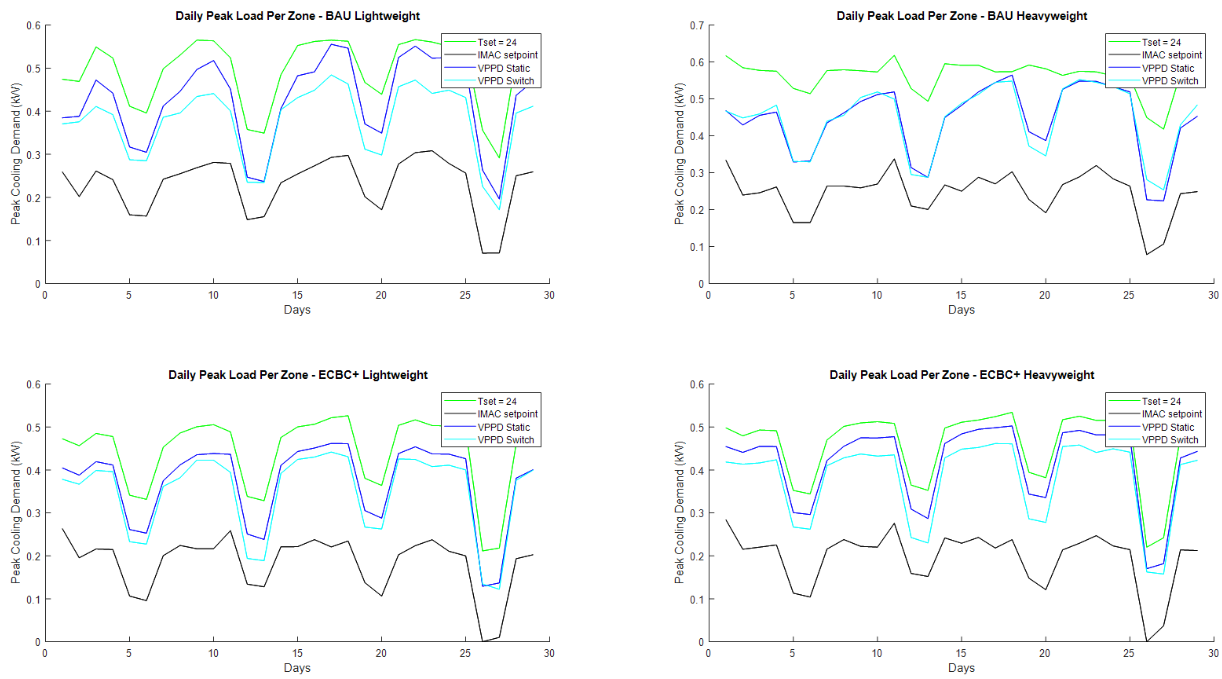

Figure 6 - Peak cooling load comparison for the Month of May

Between the VPPD static and VPPD Switch approaches, except for the BAU HW building variant, the peak load for the VPPD Switch control is observed to be constantly lower. In Figure 7, the average peak loads is compared across all 16 scenarios, showing that the ECBE+ LW building variant leads to the lowest absolute peak load for all setpoint control strategies implemented. The ECBC+ LW corresponds to a high thermal resistance and low thermal mass in the building fabric, suggesting that an increase in thermal mass of the building as implemented through varying wall thickness is not a suitable strategy for peak load shaving. It is possible that the lag in heat transmittance introduced by the heavier building fabric is not large enough to offset the cooling demand to non-peak conditions. For the example afternoon, it can be seen that the high temperatures persist over a number of hours. Thus, for the thermal mass based strategy to be successful, the lag in heat transmittance should be of the same order. Clearly, increasing the thickness of the fireclay brick by 30cm within the external wall likely does not have this effect. However, the increase in thermal resistance has a significant effect on reducing the peak load. Table *3* provides the percentage reduction from the baseline (Tset=24), across the remaining three setpoint control strategies and all building variants. In all cases, the IMAC standard results in a reduction by more than 50%. For the remaining two setpoint control methods, VPPD Switch results in a lower peak load for all scenarios expect BAU HW. Considering that the absolute peak load is lowest for the ECBC+ LW building variant, following the IMAC based control, the VPPD switching method results in the lowest peak load, corresponding to a reduction of 20.5% from the baseline setpoint control.

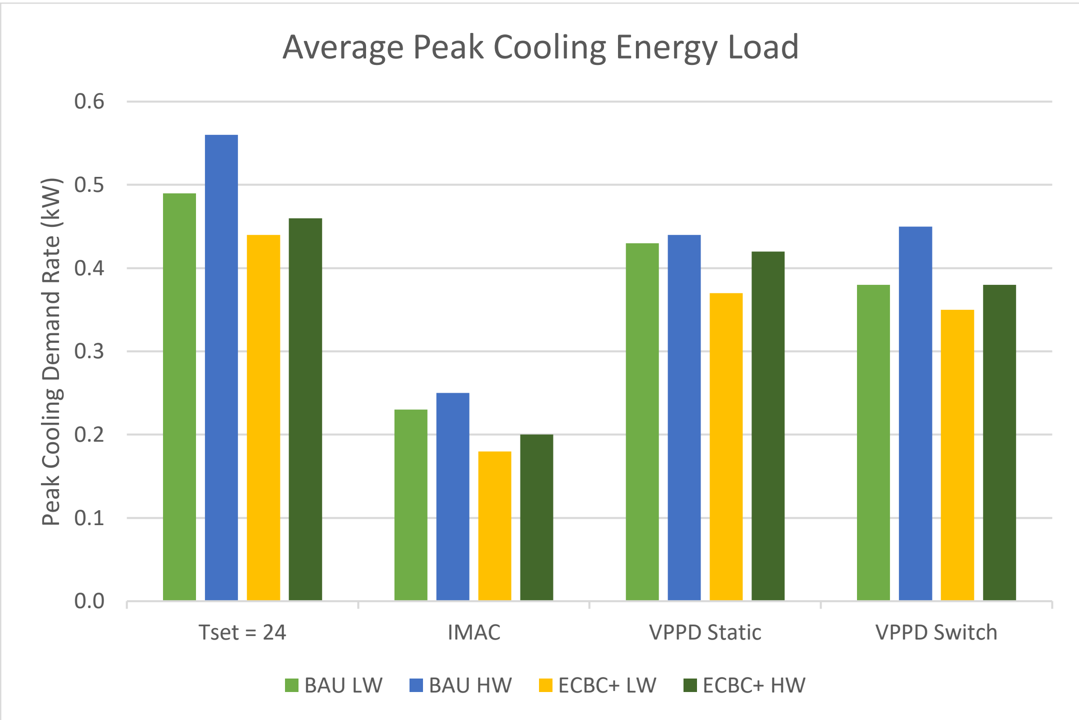

Figure 8 - Average peak load comparison

Table 3 - Reduction in peak load from the baseline

	Average peak load Reduction from baseline (%)		
	IMAC	VPPD Static	VPPD Switch
BAU LW	53.1	12.2	22.4
BAU HW	55.4	21.4	19.6
ECBC+ LW	59.1	15.9	20.5
ECBC+ HW	56.5	8.7	17.4

Table 4 and Figure 9 provide the energy demand results for the same simulation period over the 16 scenarios. The same trends that were observed for peak loads analysis are also present for the total energy demand. Again, the ECBC+ LW building is the most energy efficient building variant. Here, significant reductions in the monthly energy demand are observed compared to the baseline. The IMAC, VPPD static and VPPD Switch control methods lead to monthly energy demands of 23.1kWh, 109kWh and 102kWh respectively, corresponding to a reduction of 86.7%, 37.1% and 40.6% from the baseline respectively. The analysed zone has a covered area of 6.8m^2. Extrapolating to the building level, that has a total covered area of 330m^2, implementing the IMAC and VPPD Switch setpoint control methods for the ECBC+ LW building variant in comparison with the BAU LW with Tset=24 baseline, results in a reduction of average daily peak load and total energy demand by 60% and 20% respectively, corresponding to a reduction of 14.6kW and 4.9kW peak load respectively at building scale. Again, it should be noted here that the IMAC standard is not subject to the PMV/PPD metric that indicate highly uncomfortable indoor conditions for the setpoint control method.

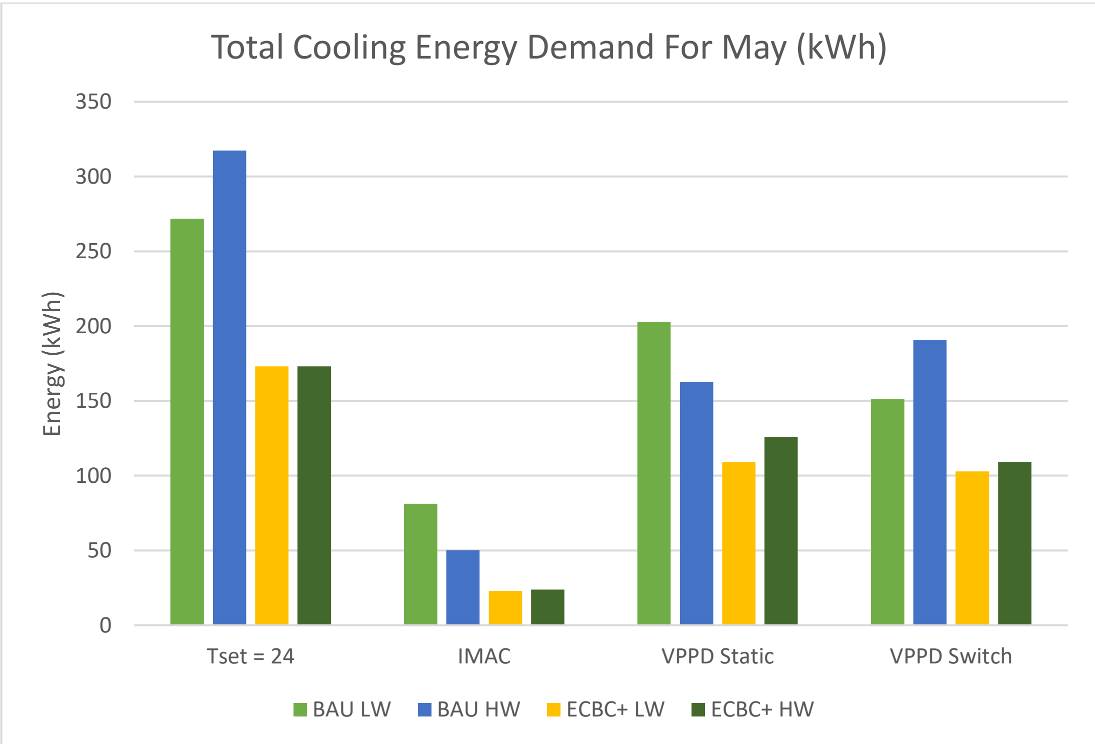

Figure 9 - Total monthly energy demand comparison

Table 4 - Reduction in cooling energy demand from the baseline setpoint control of Tset =24

	Total cooling demand Reduction from baseline (%)		
	IMAC	VPPD Static	VPPD Switch
BAU LW	70.1	25.3	44.3
BAU HW	84.2	48.7	39.9
ECBC+ LW	86.7	37.1	40.6
ECBC+ HW	86.3	27.2	36.9

In order to further understand the impact of different cooling setpoint control approaches applied, the energy quality aspect is considered here. As the temperature of thermal flows vary, their work potential varies accordingly. The concept of exergy has been widely used to analyse energy flows to account for energy quality in addition to its quantity (Dewulf *et al.*, 2008; Dincer and Rosen, 2012; Khattak, 2016). For a thermal flow of fixed quantity, its work potential and exergy content varies according to variation in the temperature of the thermal flow as well as that of the outdoor environment, given by the equation below.

$$\dot{E}x_{Thermal\ flows} = \dot{Q}(1 - \frac{T_{out}}{T})$$

Where,

$\dot{E}x_{Thermal\ flows}$ *is the exergy flow rate of the thermal flow* $\dot{Q}$ *at a temperature* T
T_{out} *is the outdoor air temperature*

Consequently, this has led to the development of the 'Low Ex' approach in buildings, that promotes matching of the energy quality in supply and demand (Schmidt and Ala-Juusela, 2004; Khattak *et al.*, 2016). Much work has been done to analyse building systems exergetically (Hepbasli, 2012), as it provides a deeper understanding of the energy required to condition building space. Therefore, the cooling exergy demand for analysed zone, for the most energy efficiency building variant (ECBC+ LW) is calculated using the preceding equation. The cooling exergy demand for the baseline and VPPD Switch scenario are depicted in Figure 10 which shows that the individual peak values of the VPPD Switching method are higher than for the fixed 24°C setpoint. However, the VPPD switching scheme allows intermittent switching 'off' of the AC systems, resulting in cumulative reduced monthly exergy demand. For the fixed 24°C and the VPPD Switch methods, the monthly exergy cooling demand for the simulated period was 13.7kWh and 8.8kWh respectively, a reduction of 35.2% over the baseline. For the same scenario comparison, the VPPD Switch method resulted in a greater energy demand reduction of 40.6% over the baseline. The VPPD switching strategy allows temperature variation from 18°C - 30°C, thus operating at a greater difference from the outdoor environment in comparison with the baseline. This results in a lower quantity but higher quality of energy demand compared to the fixed 24°C setpoint. Additionally, the low absolute values of exergy demand highlight that while the quantity of energy may be substantial, the quality of energy required is low, as it is at little variation from the reference outdoor environment. Therefore, utilising any technology or method that may reduce the consumption of electrical energy (which is pure work) will greatly impact the exergy efficiency. An example would be the use of ground source heat pumps (GSHP) which allow utilizing the lower underground temperature to reduce the load on the AC system's compressor.

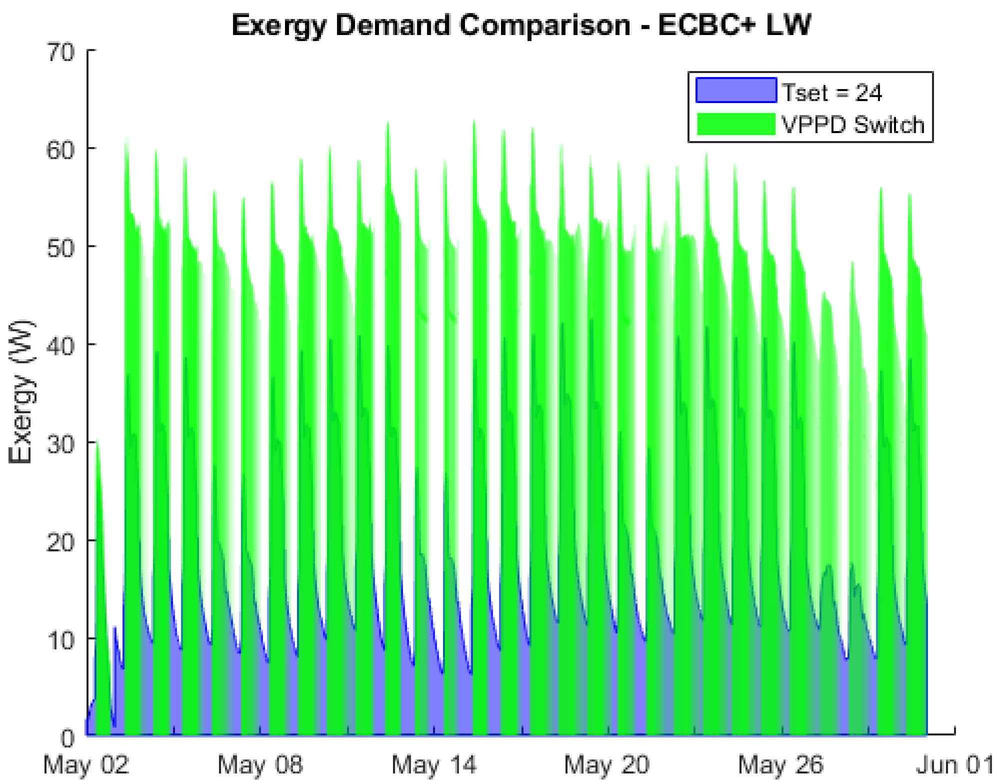

Figure 10 - Cooling exergy demand comparison

7. Conclusions and future work

In this work, a recently developed thermal comfort indicator was used for the first time as an indirect control variable for dynamically setting the indoor setpoint temperature. The model, developed by Vellei and Le Dréau (2019), is specifically suited for non-steady state indoor environments such as those observed in implementation of demand response events. Specifically, the VPPD% thermal comfort indicator was used to dynamically control the indoor cooling setpoint temperature. Specifically, four setpoint control strategies (Tset-24, IMAC, VPPD Static and VPPD Switch) where used for four building variants to analyse peak load reduction due to variation in the setpoint control strategy, as well as building characteristics. The following conclusions can be derived based on the preceding results analysis and discussion section,

- The IMAC based setpoint control results in the lowest peak load as well as monthly demand, however it is based on data from field observations and is not subject to the typical PMV/PPD or adaptive thermal comfort indicators.
- Based on the VPPD indicator, implementation of the IMAC control results in highly uncomfortable indoor conditions, with average VPPD ranging from 62% - 75%.

Therefore, there is a significant disagreement between thermal comfort prediction using PMV/PPD models and field data.

- For the setpoint control strategies subject to the PMV/PPD thermal comfort metrics, the VPPD switching scheme resulted in the lowest peak energy load as well as monthly energy demand.
- Within building characteristics variation, increasing thermal mass by varying external wall thickness was ineffective in offsetting the peak load. However, increasing thermal resistance reduced the absolute peak load as well as monthly energy demand.
- For the scenarios assessable by PMV/PPD thermal comfort theory, in this case of the typical Indian residential apartment building, the VPPD Switching based scheme results in the lowest energy and exergy demand.

In view of these conclusions, the following directions of future work are identified. First, while the IMAC based setpoint control results in the most energy efficient and reduced peak load option, currently available thermal comfort models predict highly uncomfortable indoor conditions when it is implemented. Therefore, there is a need to develop a thermal comfort model that may alleviate this disparity between prediction of state of the art PMV/PPD based models, and what is observed from field surveys.

Second, Vellei and Le Dréau (2019)'s model includes a transient component that makes it suitable for thermal comfort analysis and prediction in unsteady indoor building conditions, and it is based on the energy balance across the human body. This basis ignores consideration of energy quality, whilst not being able to directly account for material flows such as perspiration or breathing in air of varying humidity. Using exergy, not only the energy quality is accounted for, but material flows can equally well be modelled using the objective thermodynamic indicator (Khattak, Oates and Greenough, 2018; Gonzalez and Cullen, 2019). Consequently, (Shukuya and Hammache, 2002; Shukuya, 2009; Schweiker and Shukuya, 2012) have developed exergy analysis based thermal comfort indicators based on exergy analysis of the human body. The 'minimum exergy consumption rate' is used as a measure for the thermal neutral perception. As such, this approach is based on a more complete analysis of flows across the human body as compared to energy analysis, therefore it may be sensible to implement an exergy based thermal comfort model suitable for un-steady indoor conditions.

Third, the peak load per zone, serviceable by the VPPD switching scheme is based on the assumption that all of the 'off' period of the cycle can be utilised (Section 5.3.4). This could be realised by implementing cooling systems control at the building level. However, the extent to which the 'off' period of the cycle can be utilised within peak load conditions for the Indian context is not known. Therefore, future work can investigate these controls at a single or multiple buildings level.

Finally, the analysis and results presented in this work are based on 16 scenarios, using the BAU and ECBC+ standard building characteristics defined by Rajan *et al.*, (2014b). A more exhaustive analysis over a wider range will allow to develop a deeper understanding on how the building characteristics impact the peak load and energy demand for the VPPD based setpoint control.

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